Interannual sea ice variability modes in the NH

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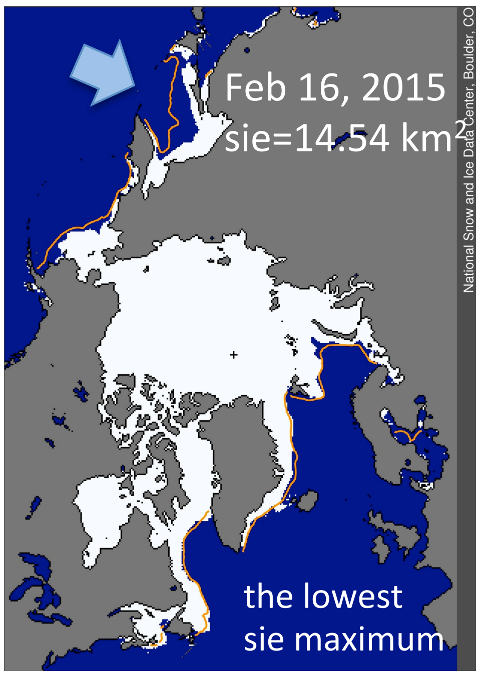
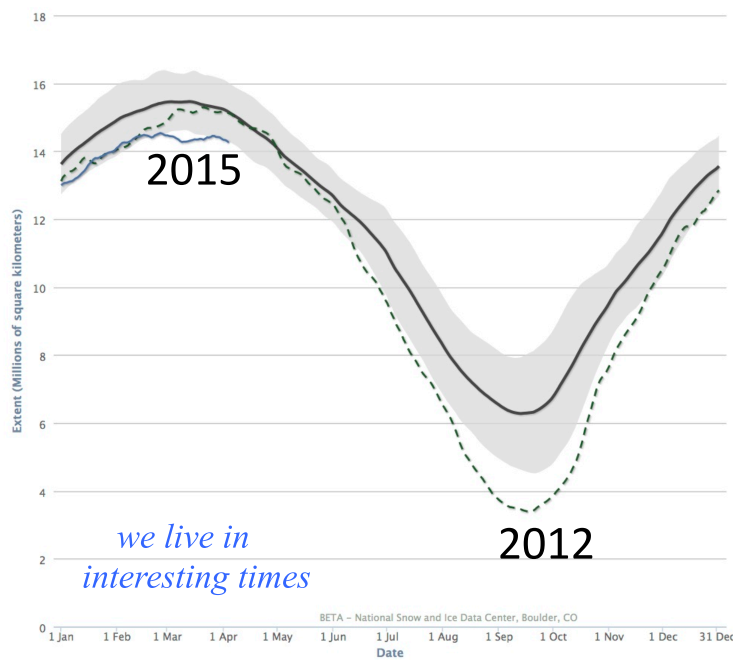
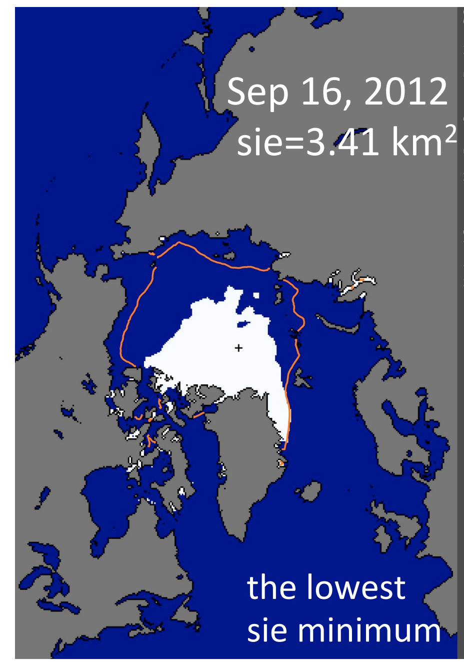




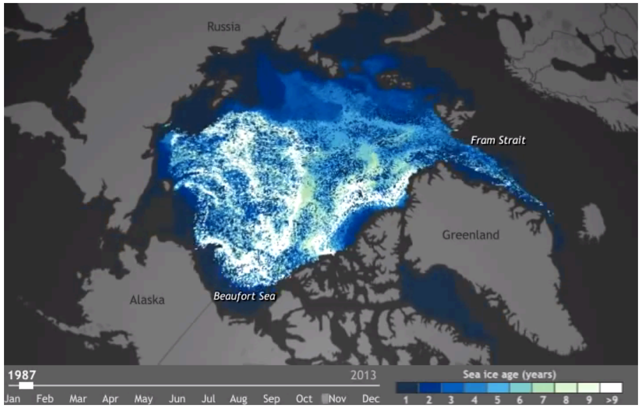


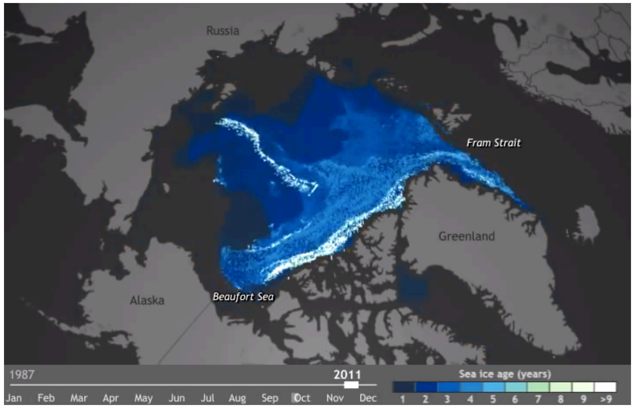
April 8, 16:00 Session 3 – Variability, at Sea Ice Prediction Workshop, University of Reading, Reading, UK, April 8-10, 2015

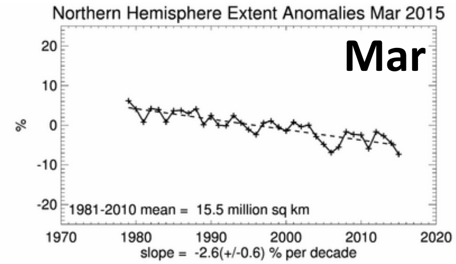
Since 1970s the NH sea ice cover has experienced a substantial long-term decline superimposed onto the strong internal variability

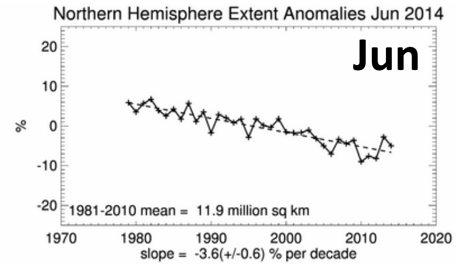
⇒ Goal to identify robust patterns of the NH sea ice variability on interannual time scales disentangled from the long-term change

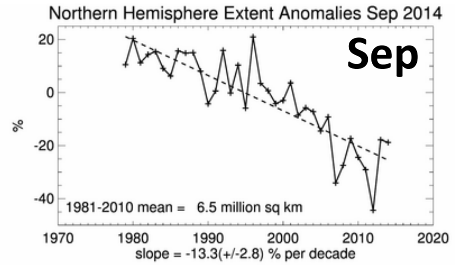
Sea ice age 1987 2011

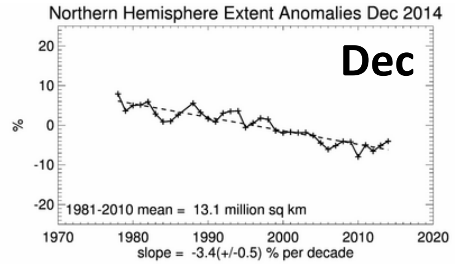




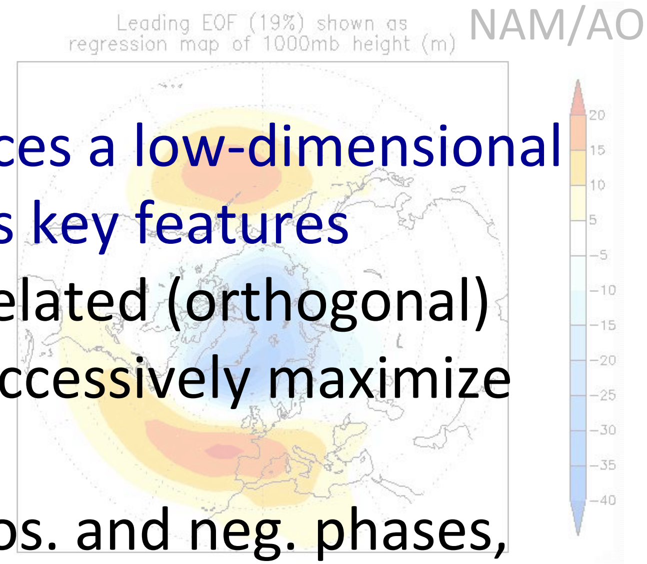








• Unsupervised learning methods



Principal component analysis (PCA) produces a low-dimensional representation of the data that summarizes key features

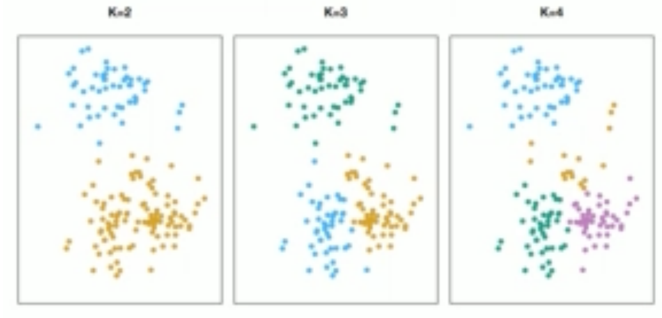
→ lin. decomposition in a set of uncorrelated (orthogonal) principal components or modes that successively maximize the variance captured

→ its limitations: symmetry between pos. and neg. phases, suppresses nonlinearity by using a lin. covariance matrix, PCA modes do not necessary represent individual physical modes, …

Clustering methods aggregate data into groups or clusters based on their distance

→ hierarchical and nonhierarchical (e.g. K-means) clustering

● K-means clustering



Simultaneously minimizes the variance between data points of a given cluster and maximizes the distance between the centers of the clusters

→ optimal number of clusters K (determined via hierarchical approach) is specified in advance and the procedure allows reassignment of data points between clusters (modes)

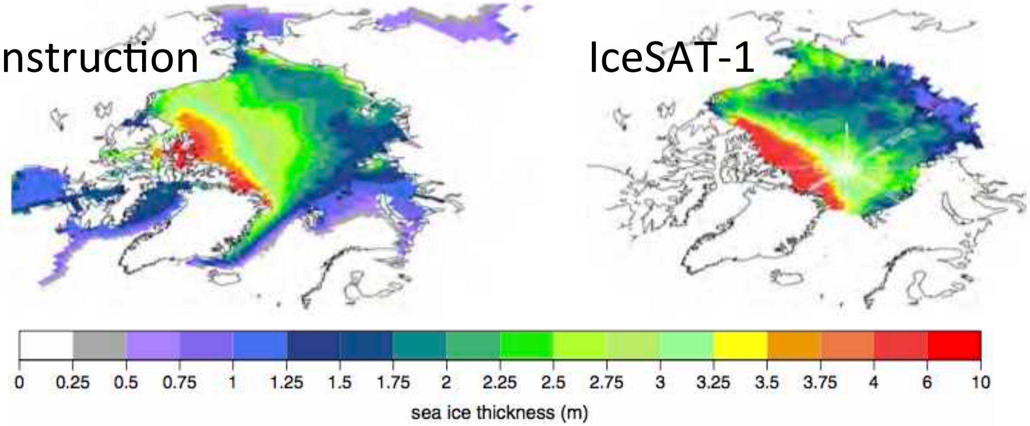
→ simplification of the large-scale variability to the K patterns of clusters (centroids) and time series of their discrete occurrence (i.e., transition between these K modes)

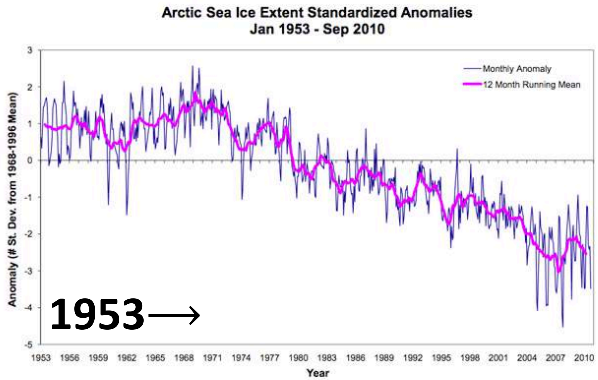
⇒ **Sea ice thickness (SIT)** is key variable - has potential to store the sea ice system memory crucial for variability and predictability on interannual time scales

● Sea ice reconstructions

Combine two sea ice reconstructions forced (DFS4/ERA-40 and ERA-Int) and nudged (ORAS4) NEMO/LIM2 (Guemas et al., 2014) to produce SIT over the 1958-2013 period

reconstruction IceSAT-1 Feb-Mar 2004-2006



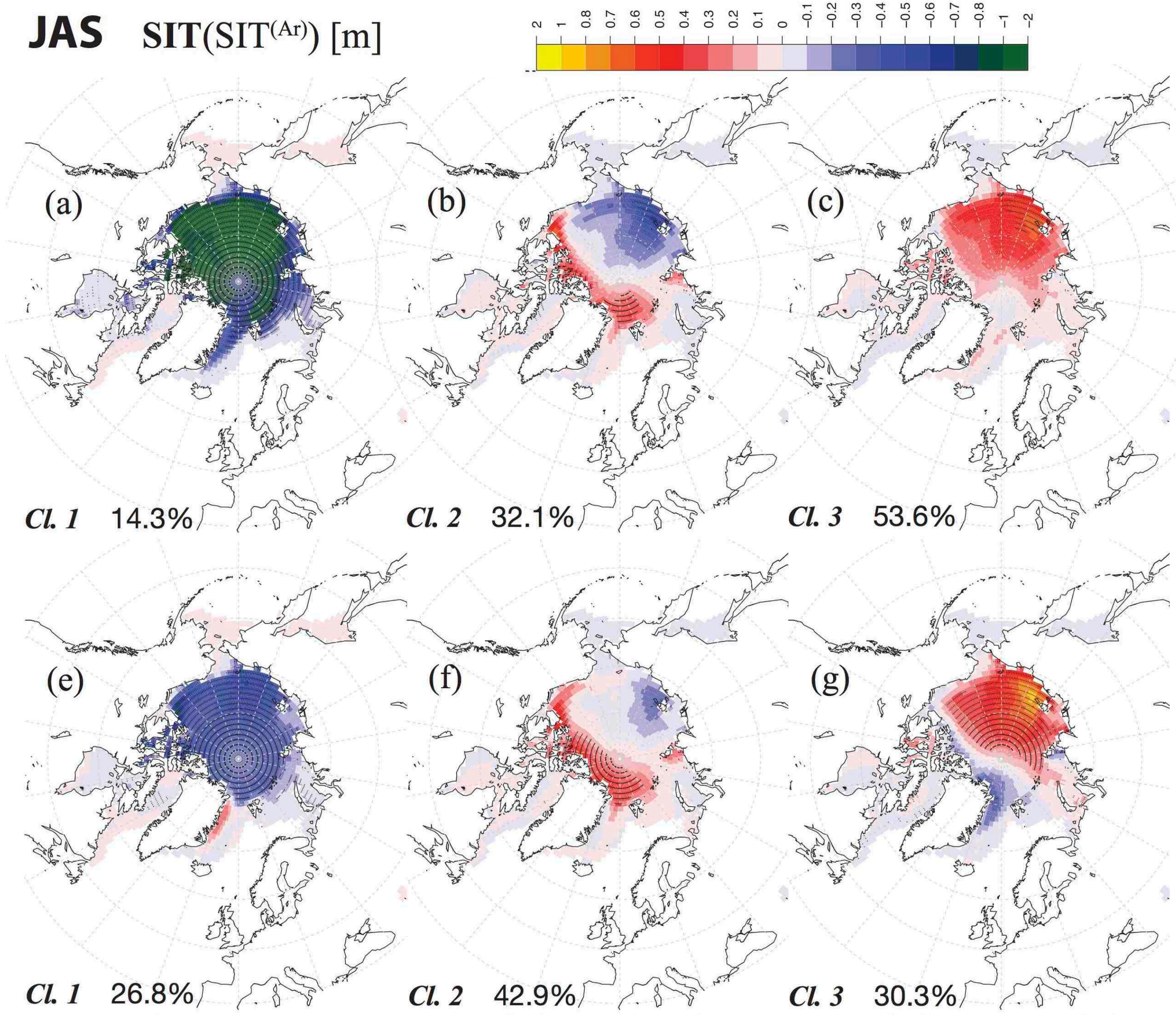


Sea ice charts of the Arctic Ocean show that ice extent has declined since at least the 1950s. Credit: NSIDC and the UK Hadley Center

Filtering out the climate change signal

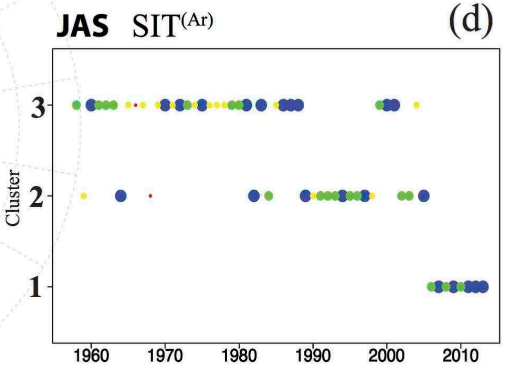
→ is linear de-trending sufficient to find robust interannual SIT cluster patterns?

JAS SIT(SIT$^{(Ar)}$) [m]

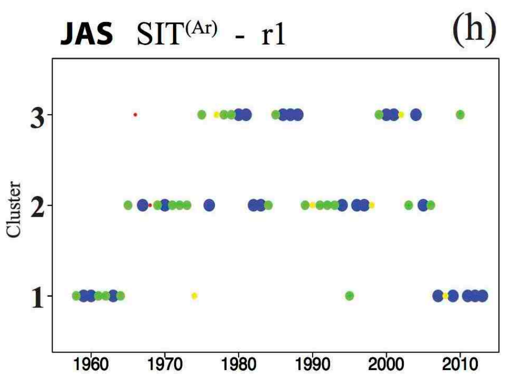


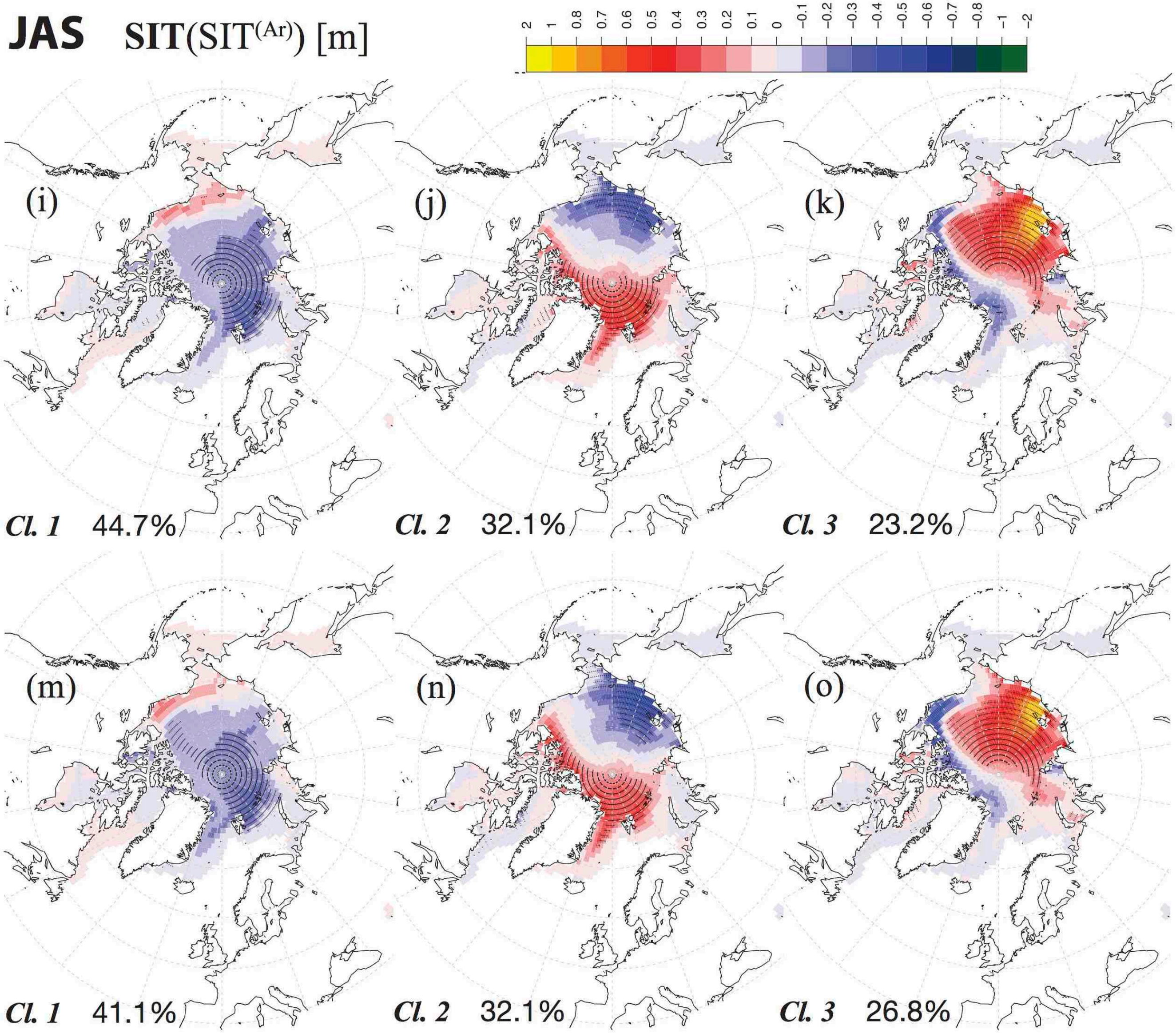
➡ K=3

- **full values**

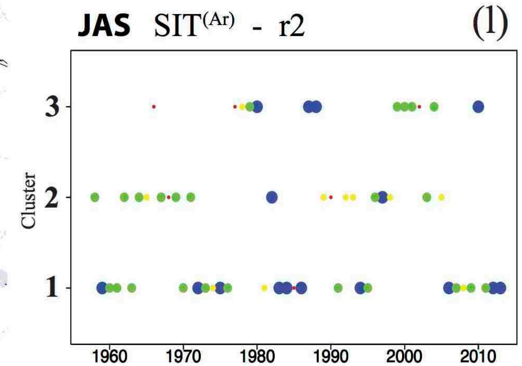


- **1st order residuals**

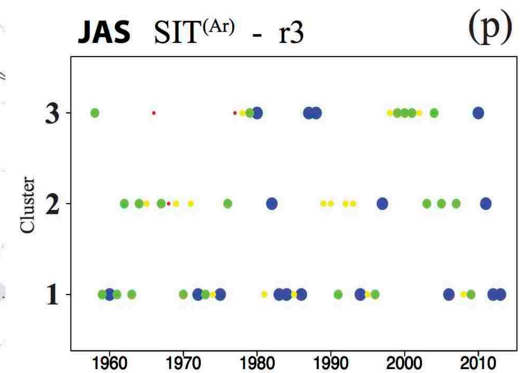




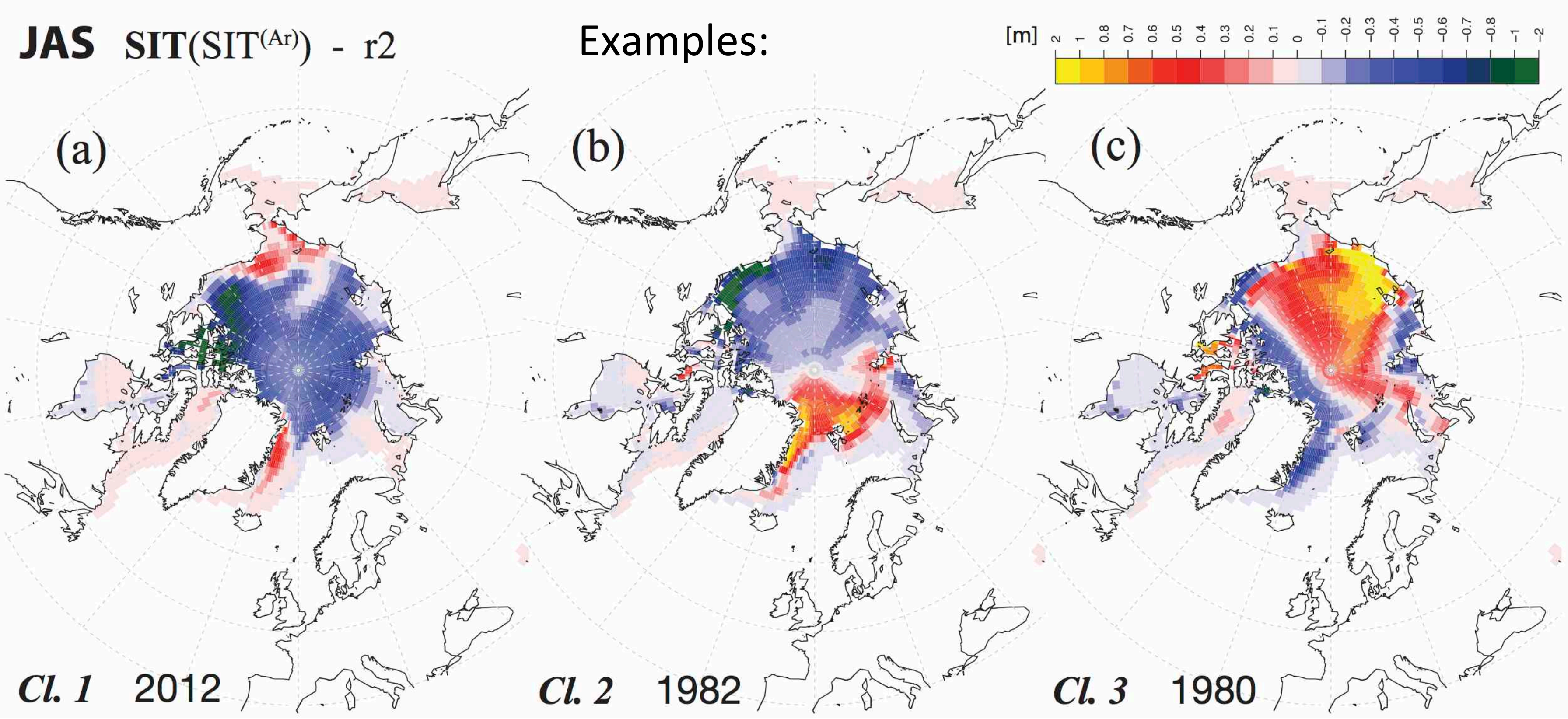
- **2nd order residuals**



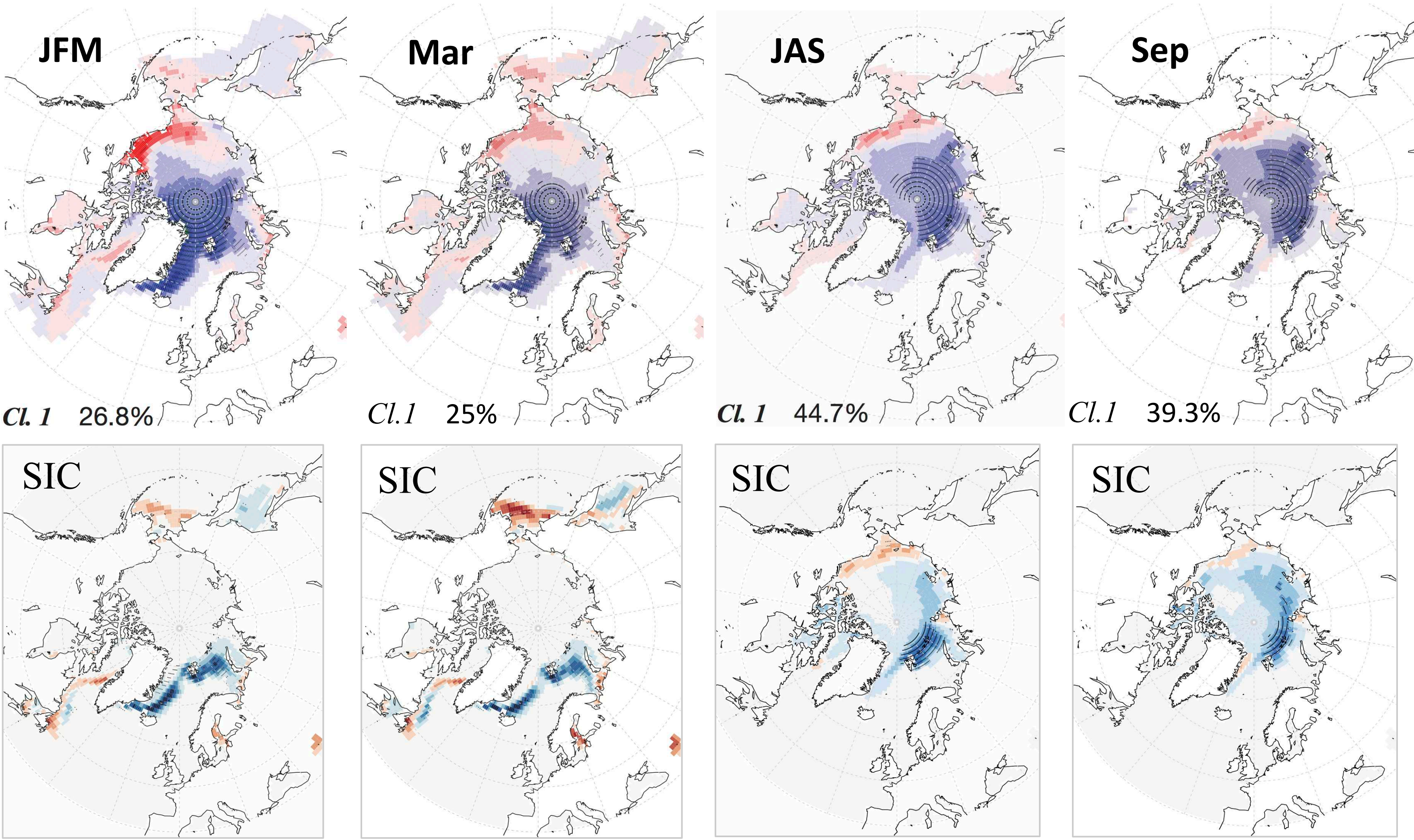
- **3rd order residuals**



⇒ Nonlinear forced response of the Arctic requires removing 2nd order polynomial approximation of the long-term climate change to determine robust interannual SIT clusters

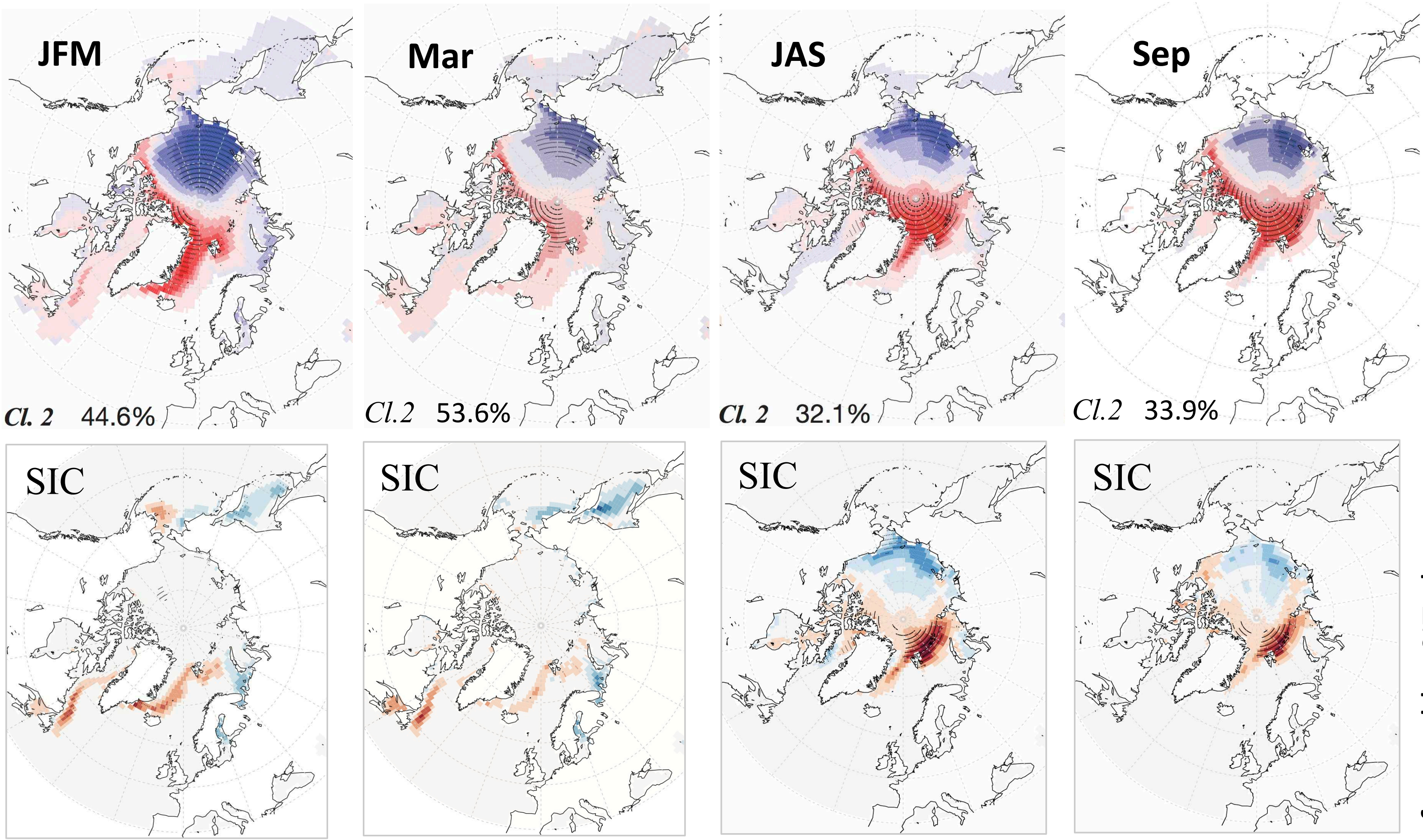


Cluster 1 = Central Arctic Thinning (**CAT**) mode $\mathbf{SIT}(\mathrm{SIT}^{(\mathrm{Ar})})$ - r2



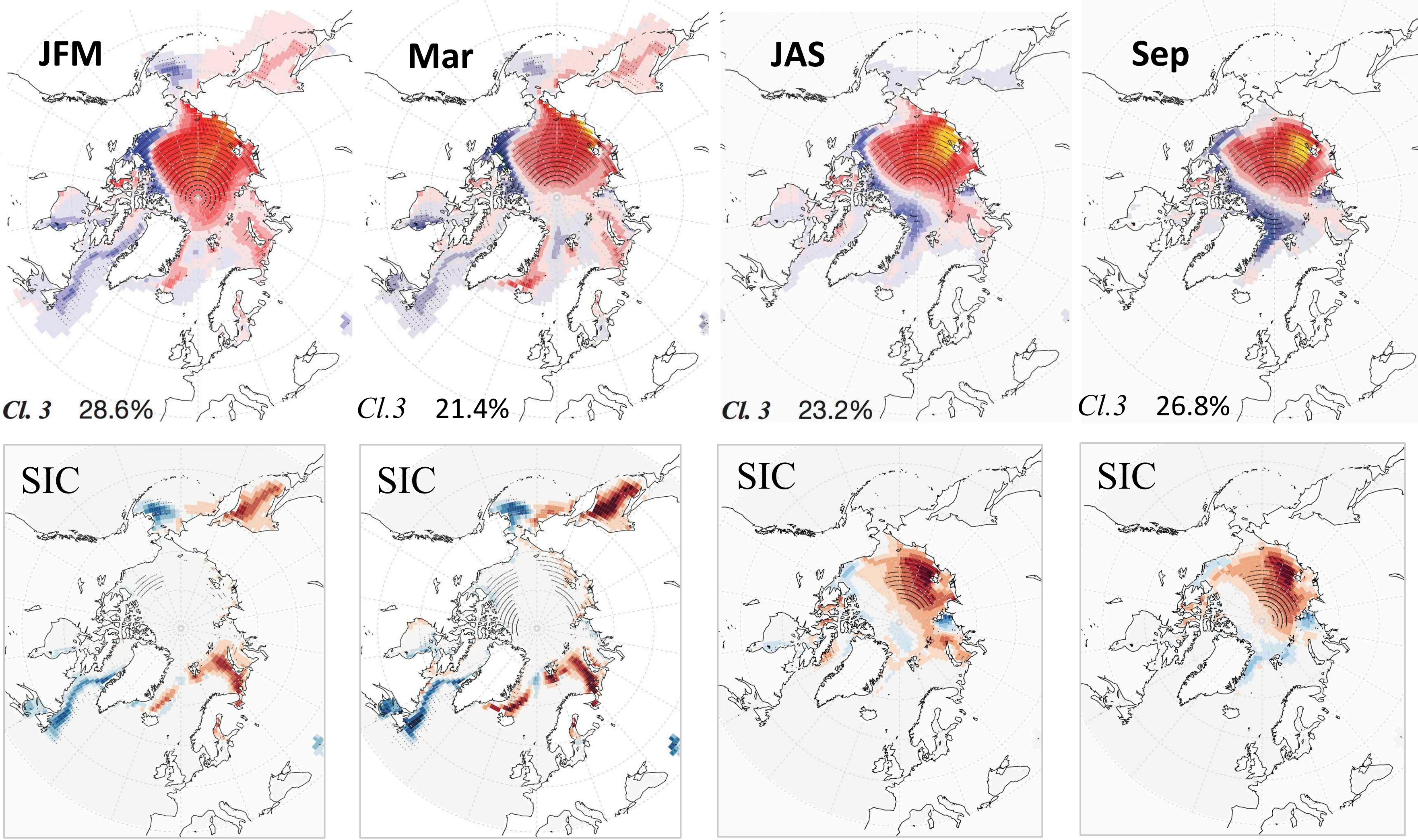
framed by SIT clusters

Cluster 2 = Atlantic Pacific Dipole (**APD**) mode $\mathbf{SIT}(\mathrm{SIT}^{(\mathrm{Ar})})$ - r2



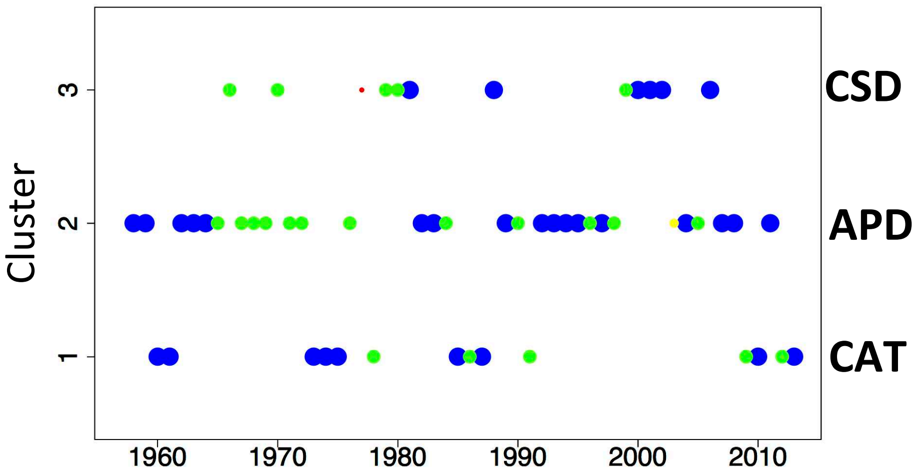
framed by SIT clusters

Cluster 3 = Canadian Siberian Dipole (**CSD**) mode **SIT**(SIT$^{(Ar)}$) - r2

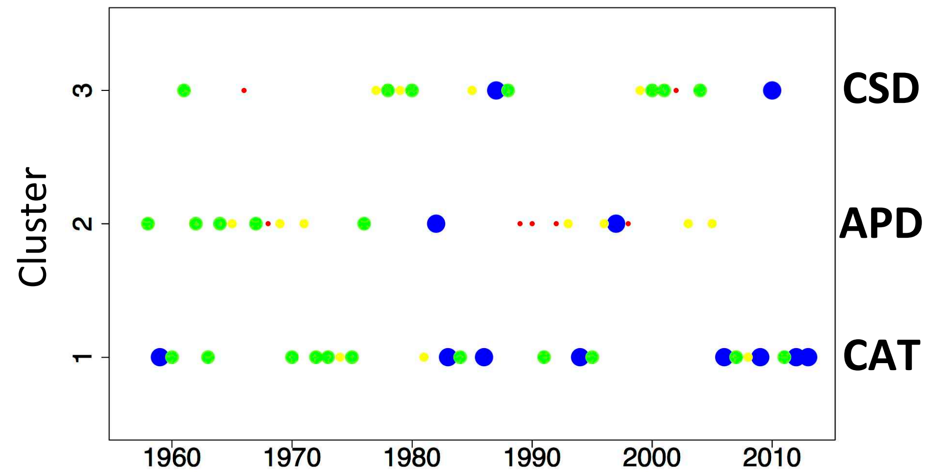


framed by SIT clusters

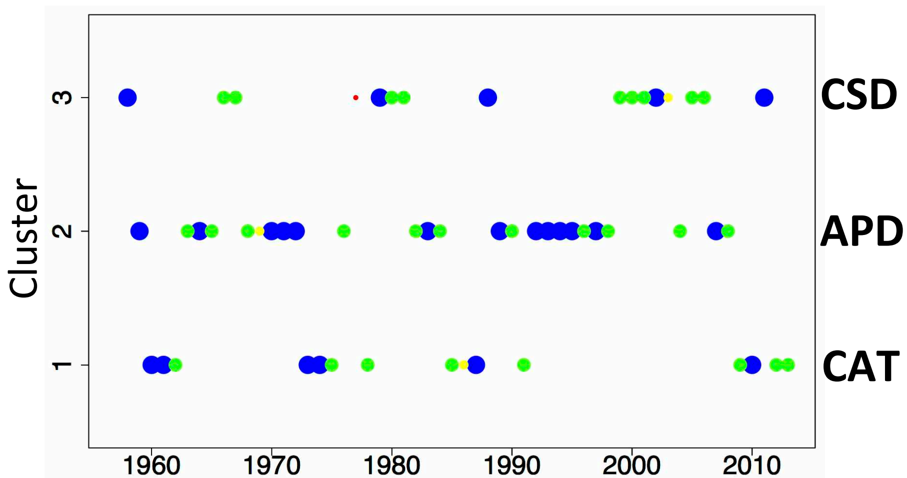
Mar $SIT^{(Ar)}$ - r2



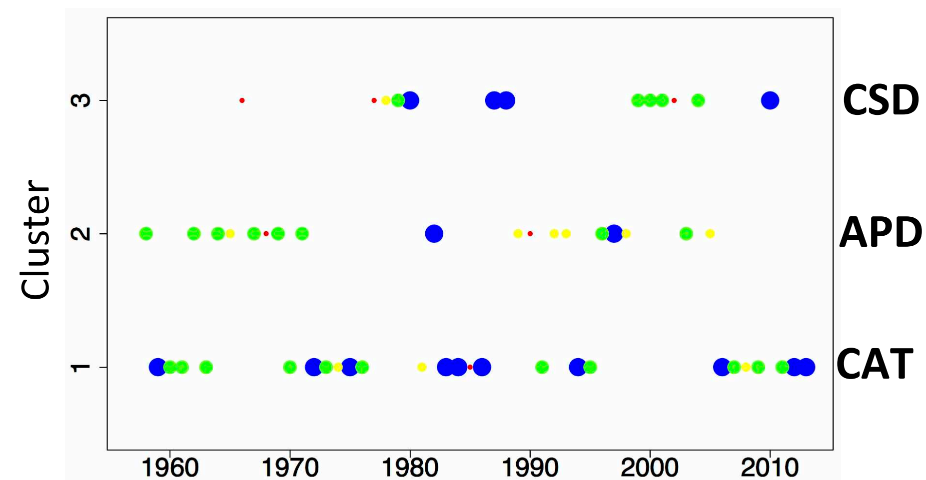
Sep $SIT^{(Ar)}$ - r2

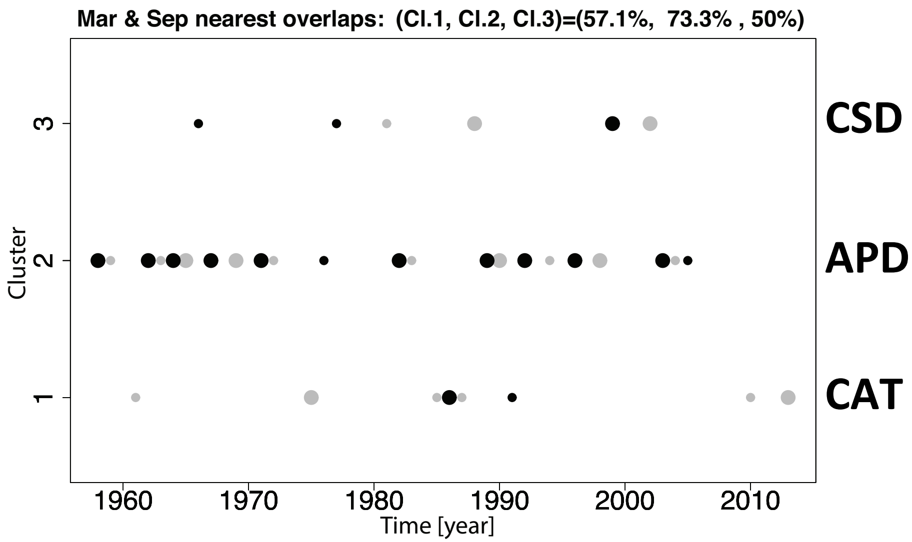


JFM $SIT^{(Ar)}$ - r2

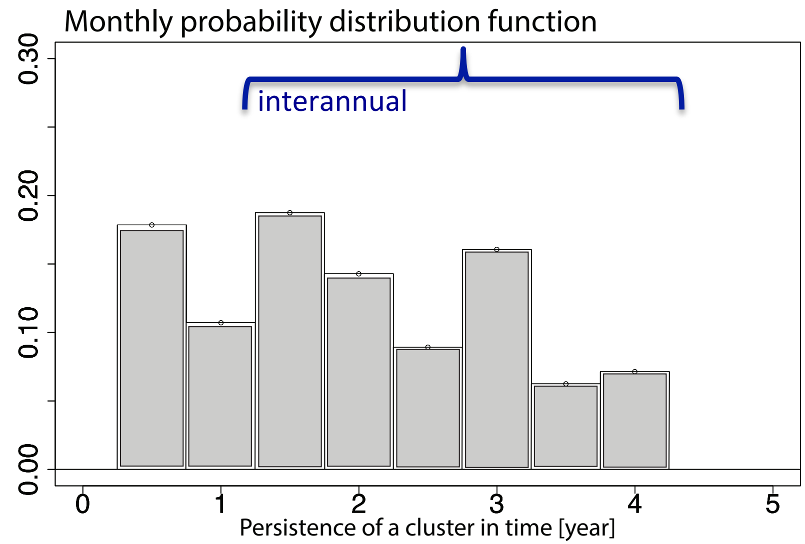


JAS $SIT^{(Ar)}$ - r2

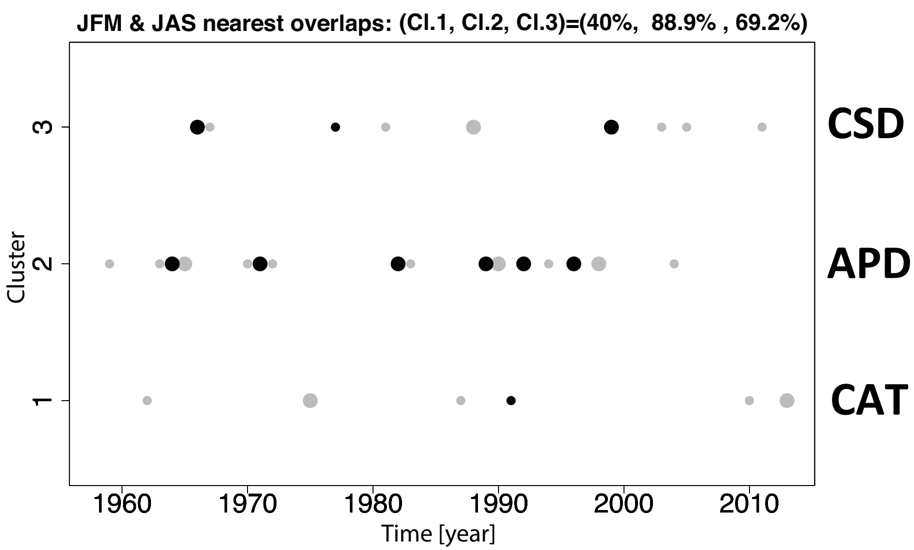




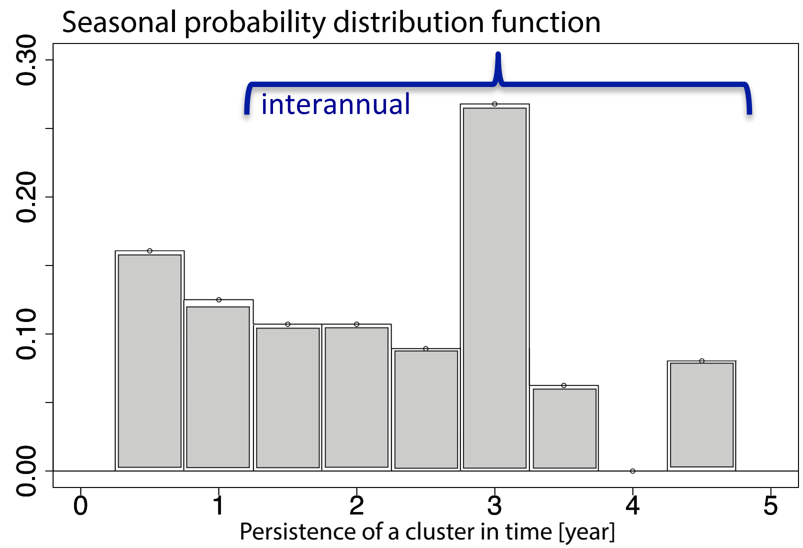
Mar & Sep nearest overlaps: (Cl.1, Cl.2, Cl.3)=(57.1%, 73.3% , 50%)
Cluster
1
2
3
1960
1970
1980
1990
2000
2010
Time [year]
CSD
APD
CAT



Monthly probability distribution function
interannual
0.00
0.10
0.20
0.30
0
1
2
3
4
5
Persistence of a cluster in time [year]

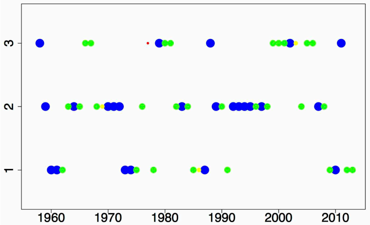


JFM & JAS nearest overlaps: (Cl.1, Cl.2, Cl.3)=(40%, 88.9% , 69.2%)
Cluster
1
2
3
1960
1970
1980
1990
2000
2010
Time [year]
CSD
APD
CAT

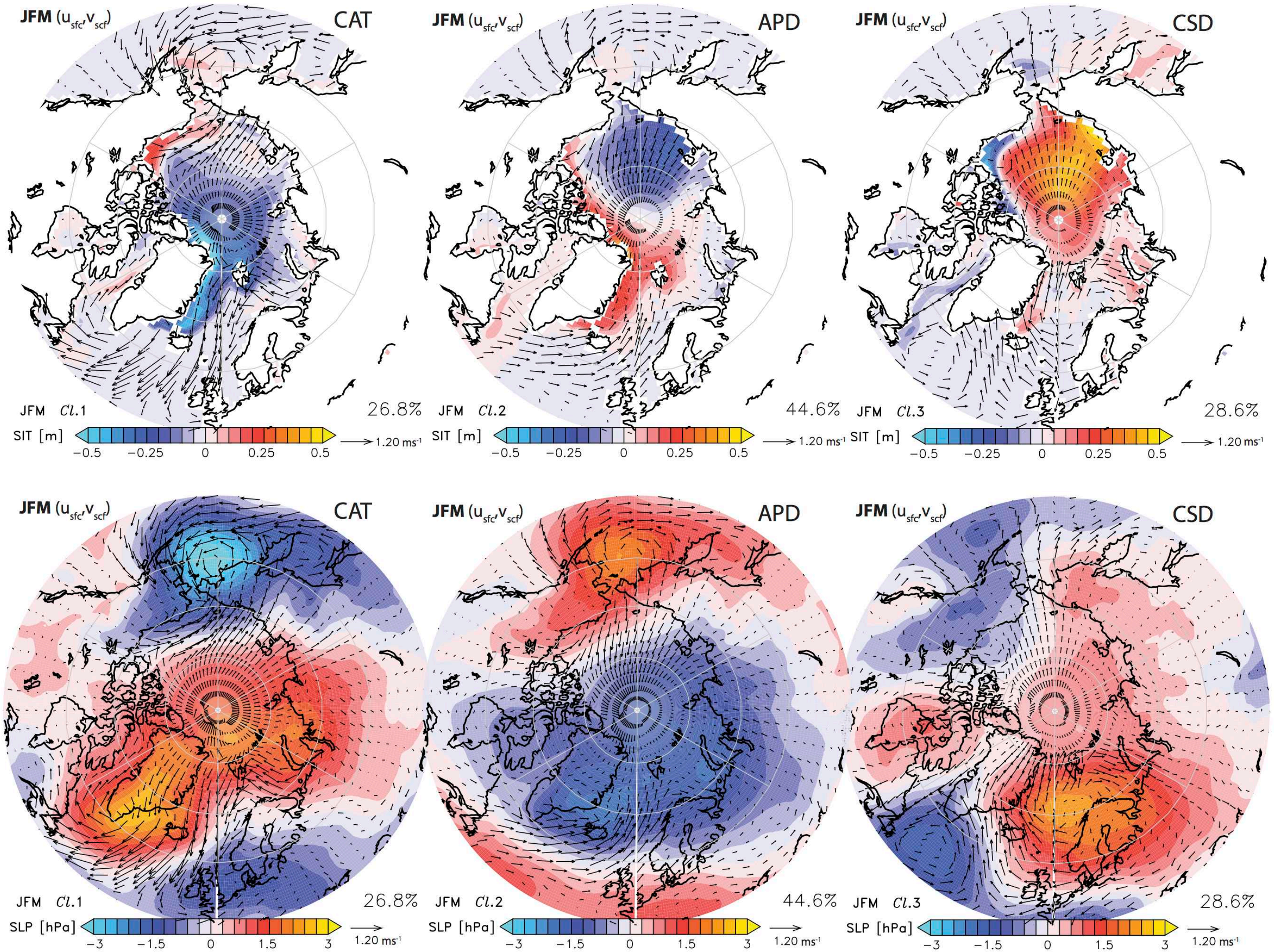


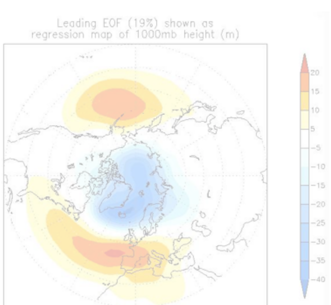
Seasonal probability distribution function
interannual
0.00
0.10
0.20
0.30
0
1
2
3
4
5
Persistence of a cluster in time [year]

JFM $SIT^{(Ar)}$ - r2



Surface wind influence is important for the form of SIT cluster patterns





NAM/AO

• Summary

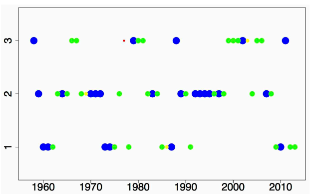
Removing 2nd degree polynomial approximation of long-term change produces robust interannual K-means cluster patterns {as well as EOF patterns}

The optimal number of the NH SIT clusters is **K=3**:
Cl. 1 = **CAT mode**, Cl. 2 = **APD mode**, and Cl. 3 = **CSD mode**, and they have consistent patterns in different months and seasons {SIT CSD pattern matches 1ts EOF pattern}

Time series of cluster occurrences has substantial persistence on interannual time scales (more than 70% probability)

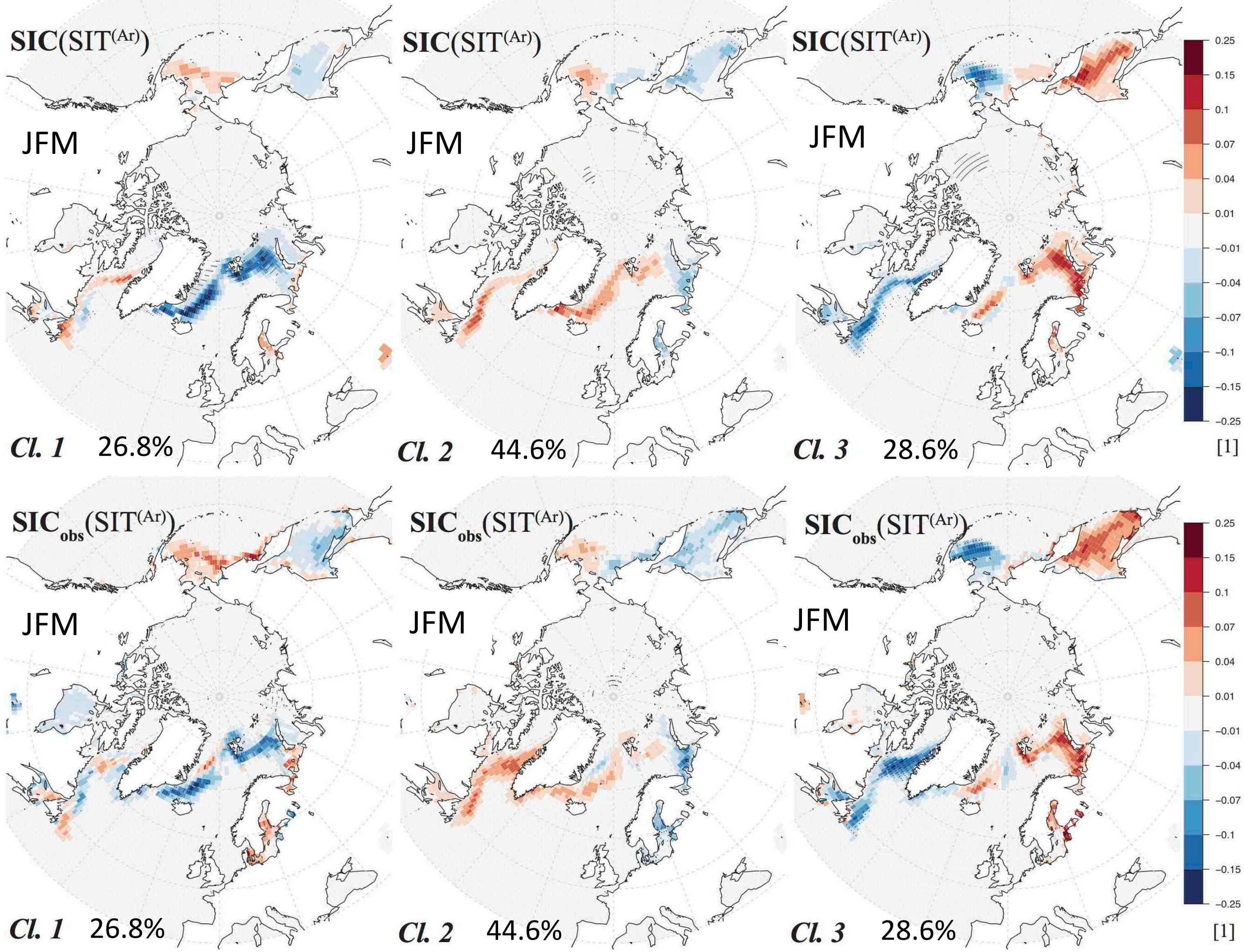
Wind (winter) is important for depositing climate information in SIT that is accumulated and released on interannual time scales

JFM $SIT^{(Ar)}$ - r2

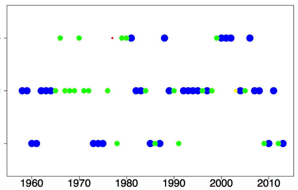


reconstruction

HadISST

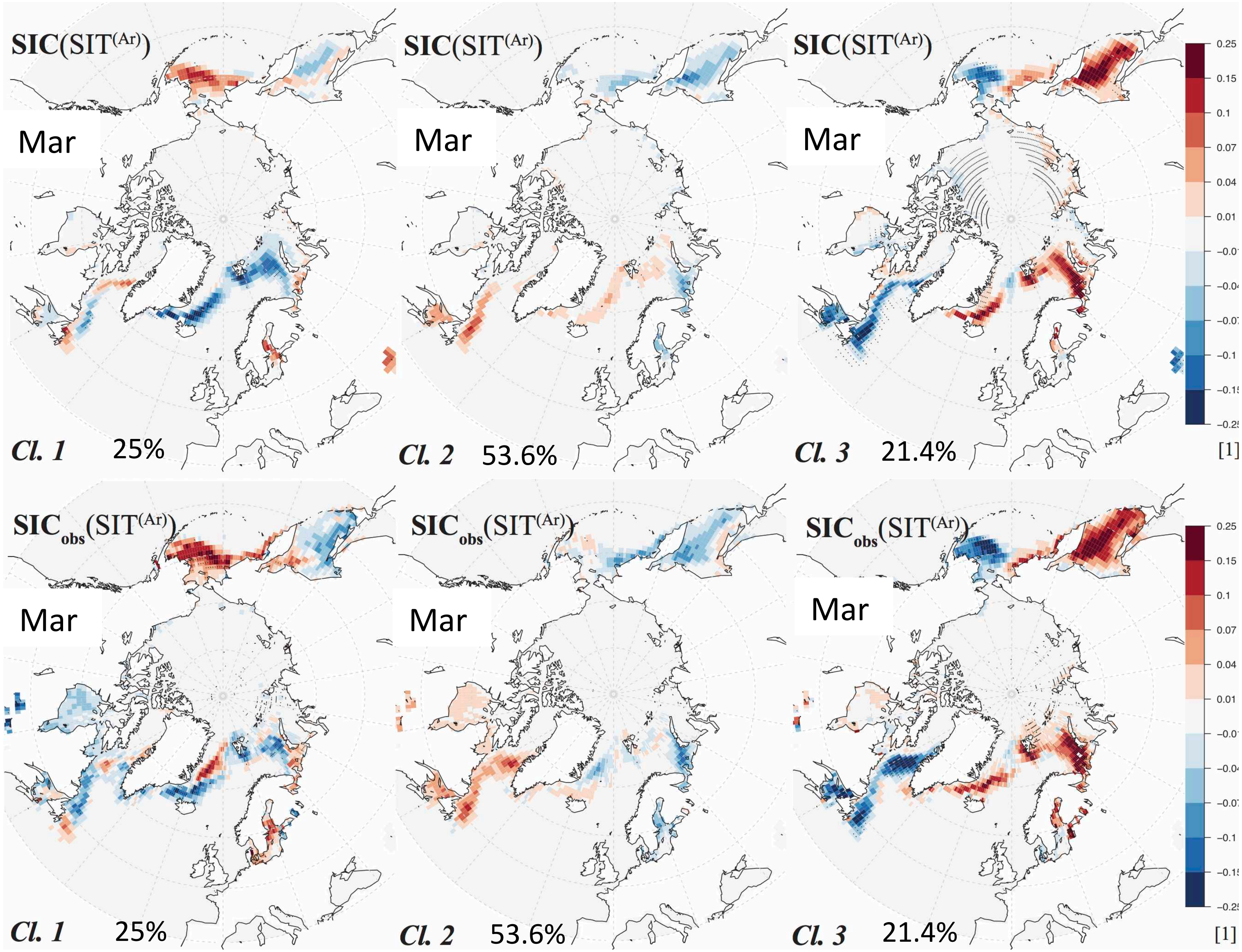


Mar $SIT^{(Ar)}$ - r2

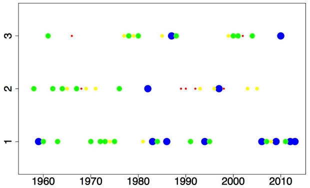


reconstruction

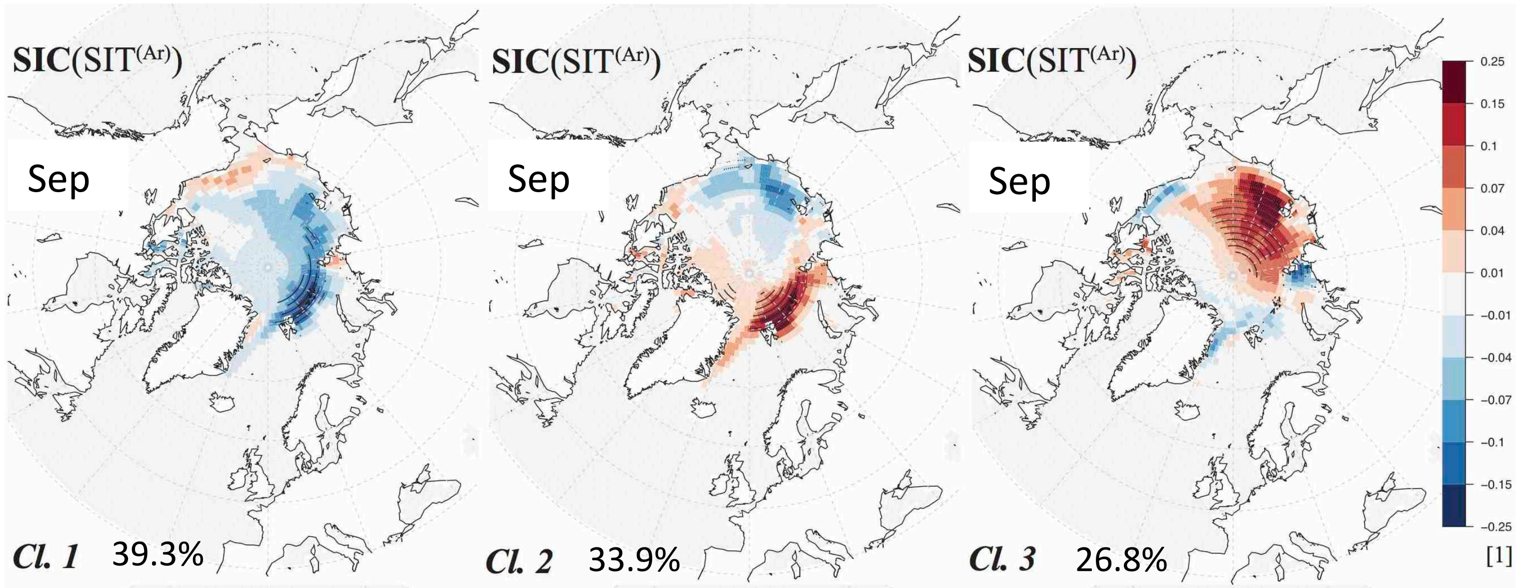
HadISST



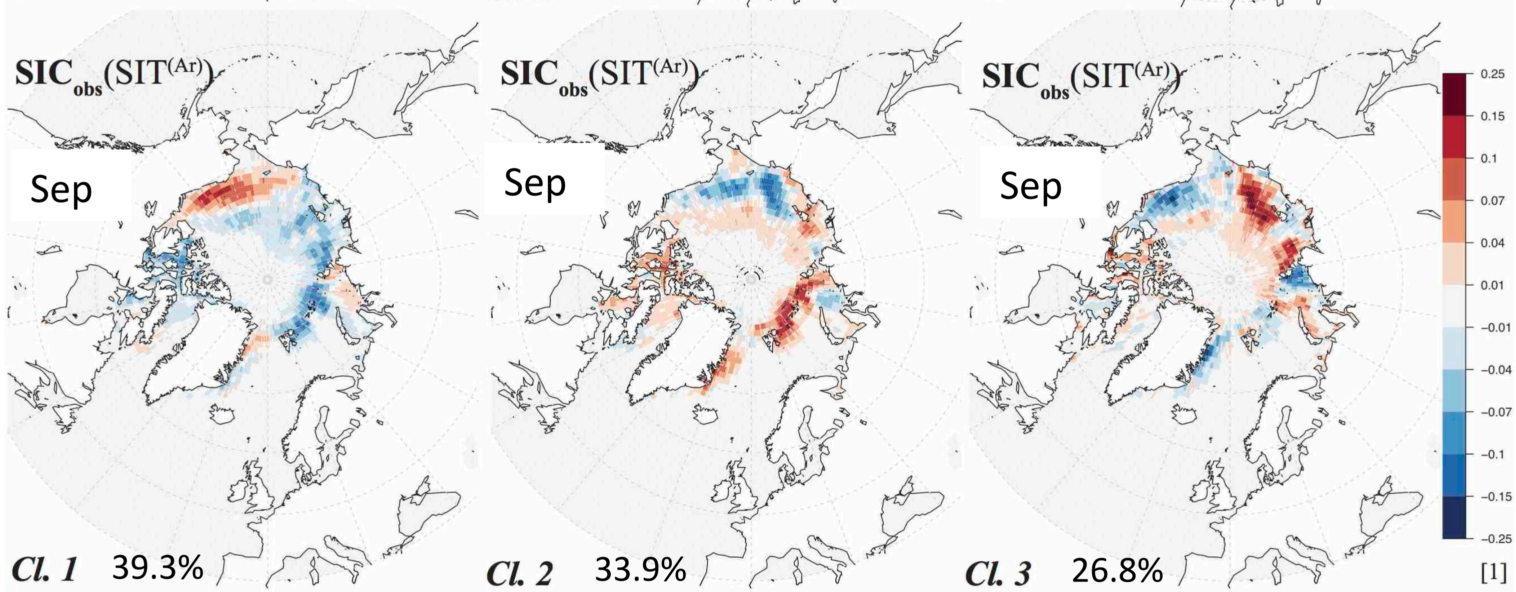
Sep $SIT^{(Ar)}$ - r2



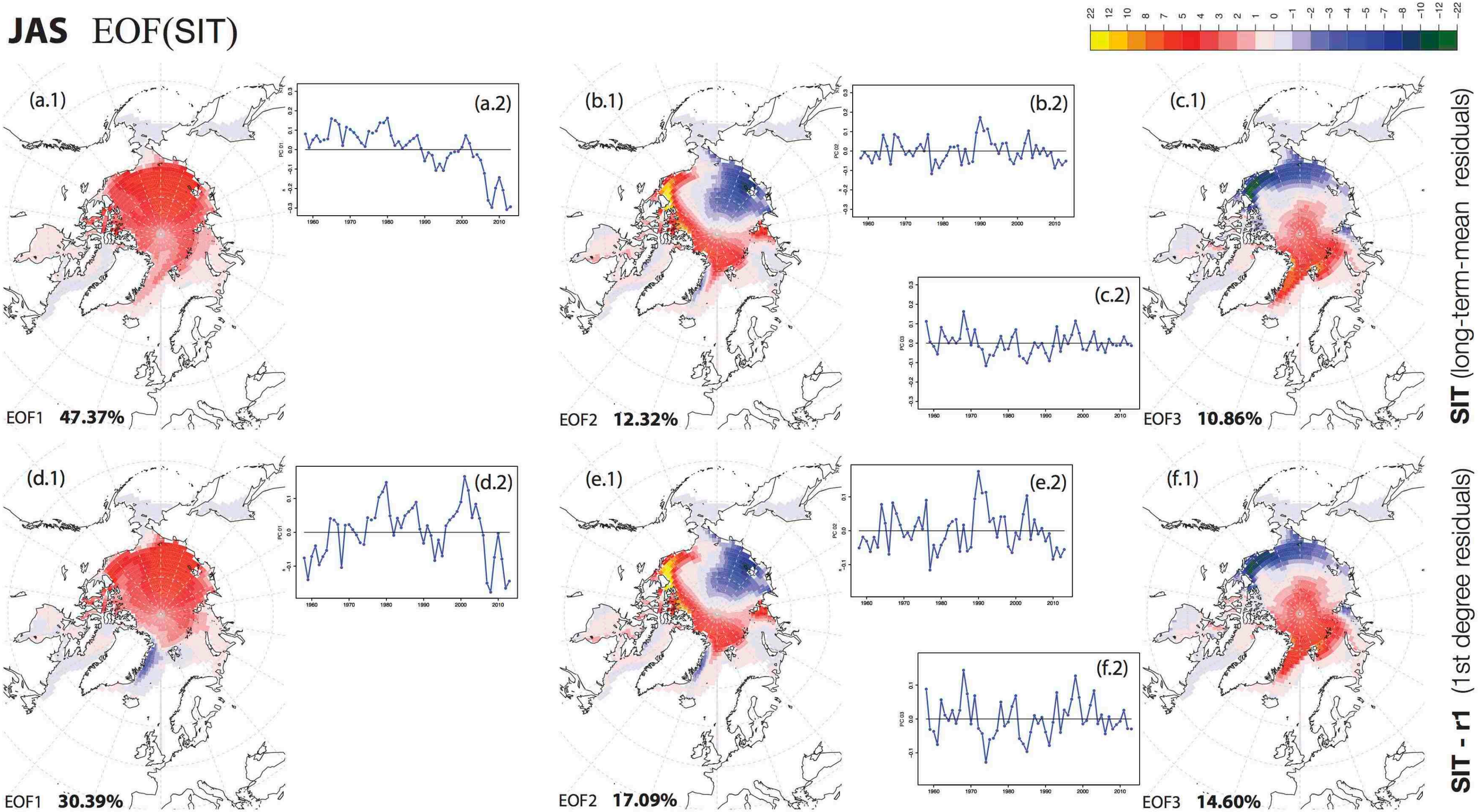
reconstruction



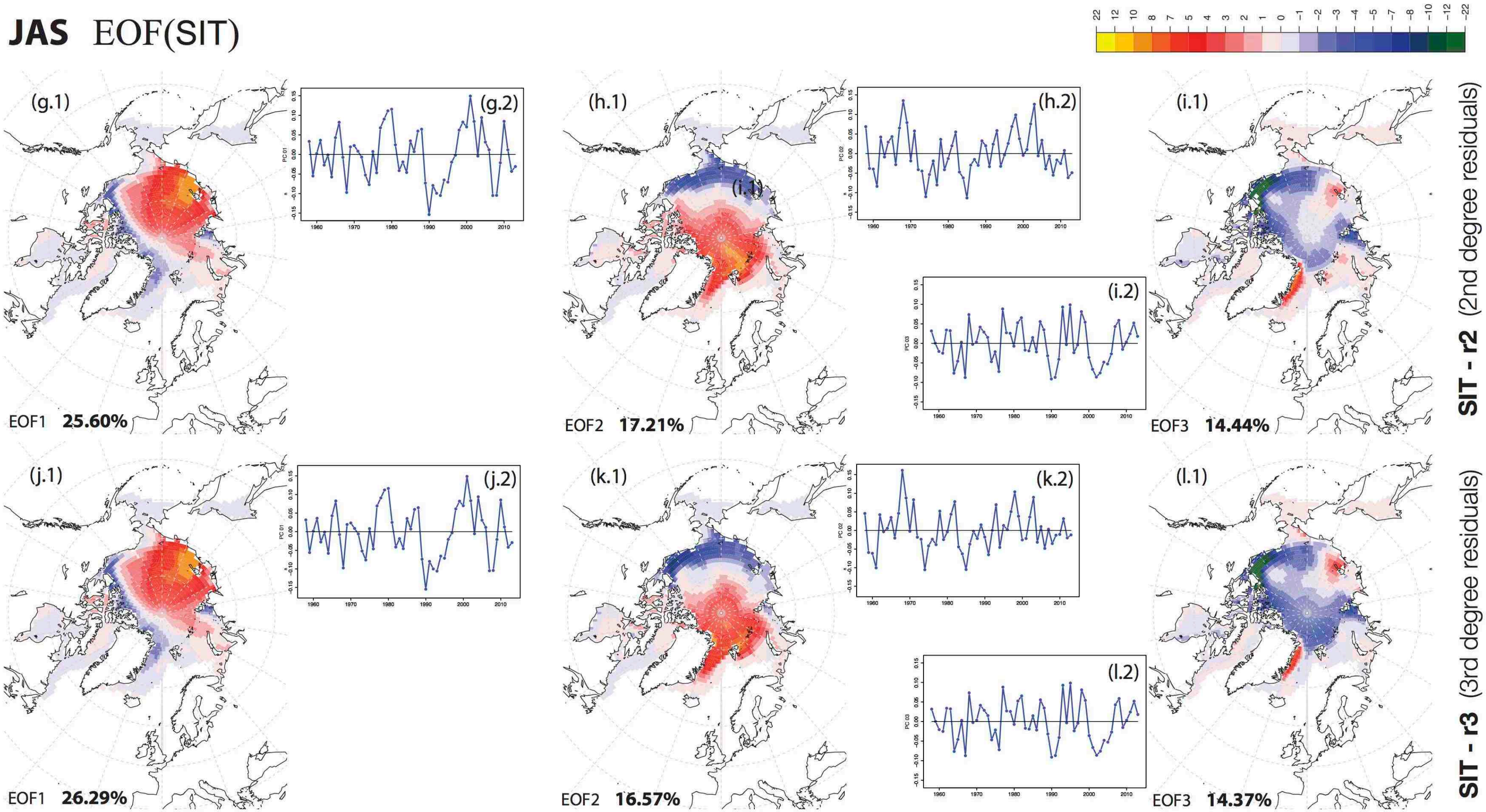
HadISST



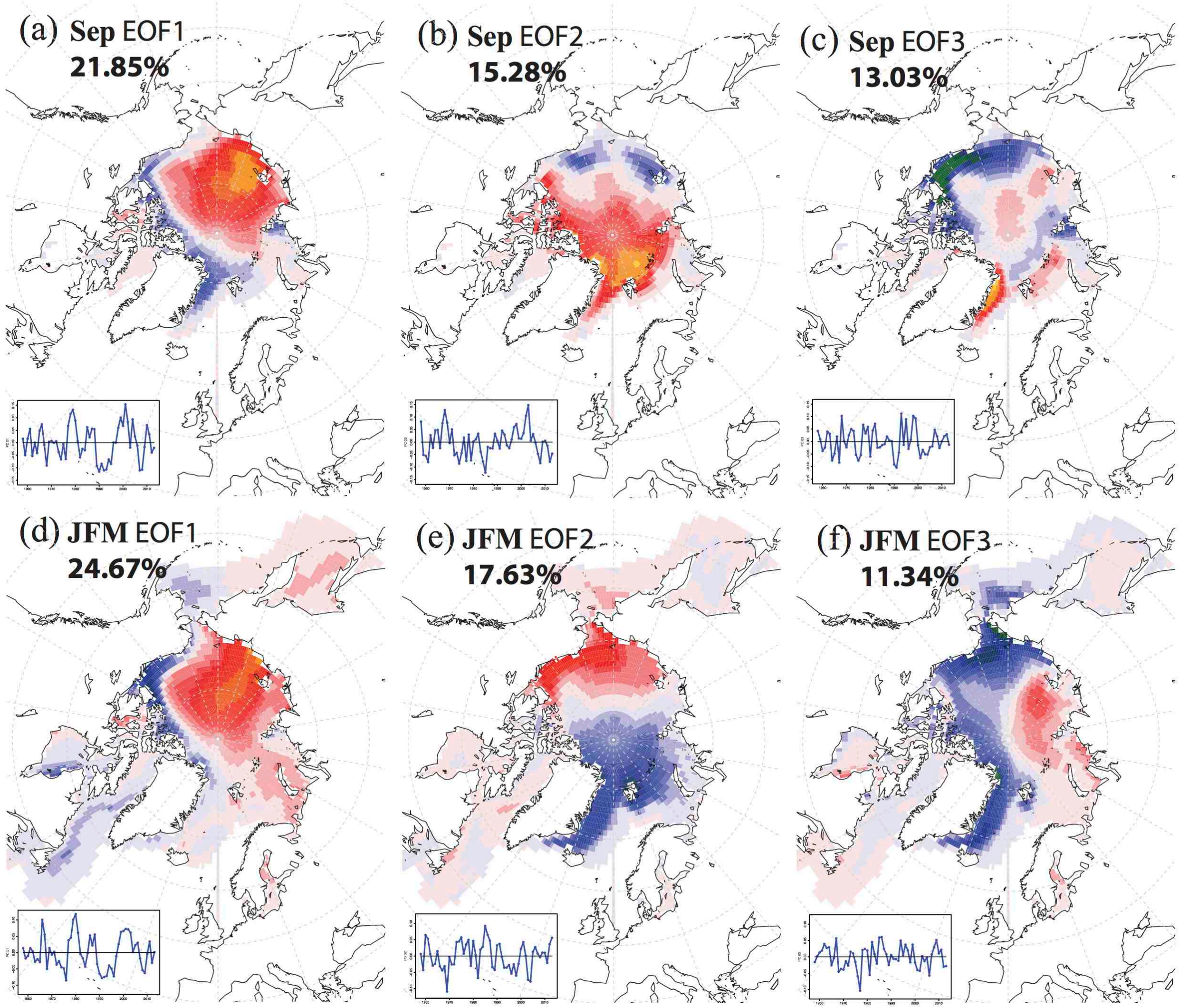
• **Connection to PCA** – is PCA also sensitive to how we approxi. long-term change?



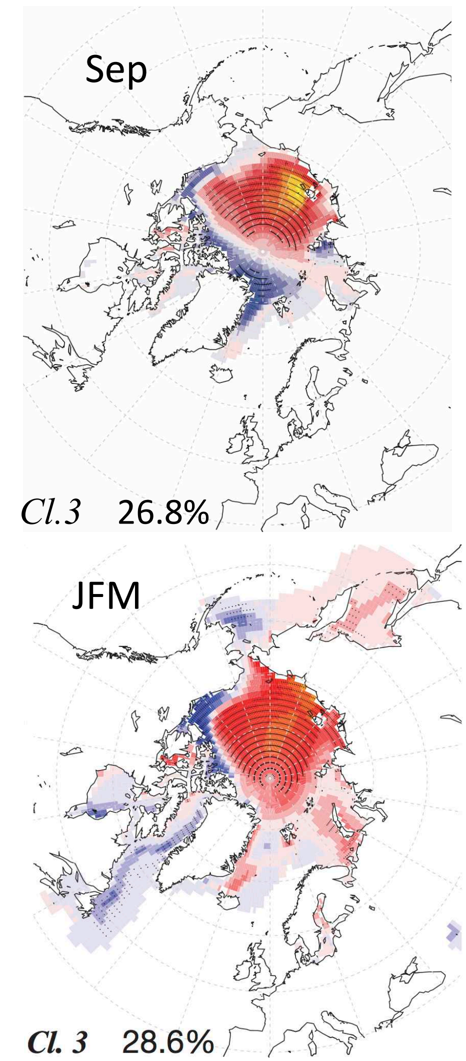
⇒ **1st EOF mode matches cluster 3 (CAT)** and also we have to remove 2nd order polynomial approximation of the long-term climate change to find robust EOFs

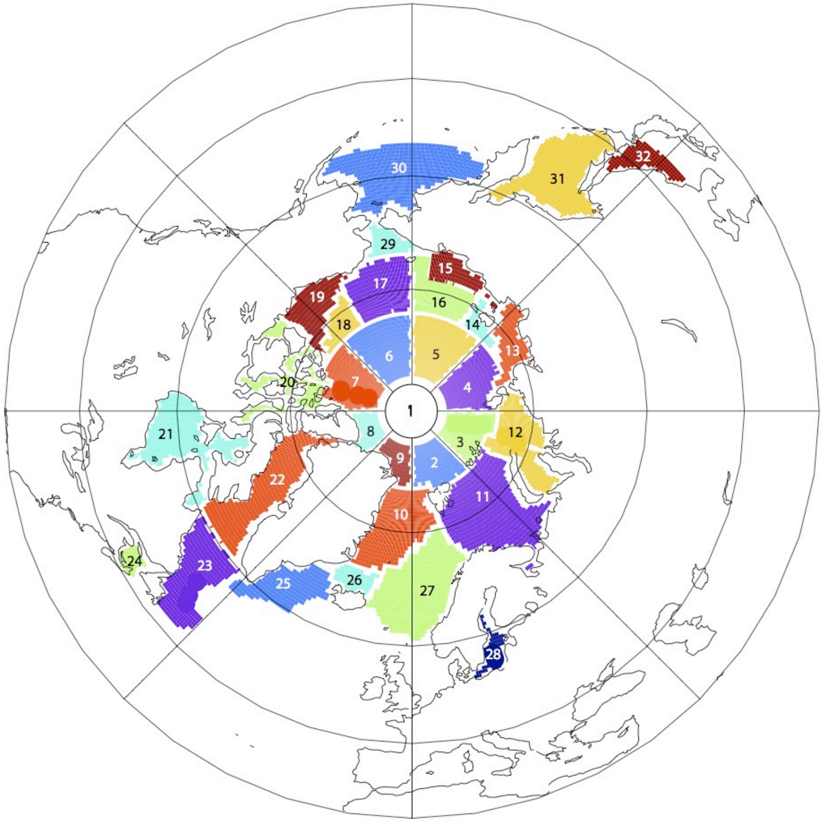


SIT - r2



CSD mode





The NH regions used to calculate the average sea ice thickness to be used for the k-means cluster analysis to increase signal-to-noise ratio and make the routine computationally efficient. From each region, we include into our analysis only the points that experience at least once sea ice presence over the 1979-2013 period in the combined sea ice reconstruction.

An example of iterative procedure of the K-means cluster analysis